IJEIT
The International Journal of Engineering and Information Technology
journal homepage:www.ijeit.misuratau.edu.ly
2022 IECMU International Engineering conference-Misurata University

Prediction of Surface Roughness in Additive Manufacturing Using Artificial Neural Networks

Fatma Wafa
Department of Material Science, College of Engineering, Misurata University, Libya
fatma.wafa@eng.misuratau.edu.ly

A.M. Abdulshahed
Department of Electrical and Electronic Engineering, College of Engineering, Misurata University, Libya
a.abdulshahed@eng.misuratau.edu.ly

Abstract— **In this work, we applied an Artificial Neural Networks (ANN) approach for prediction of the part surface roughness for 3D printing technology. A small number of neurons was used for building ANN model with the help of MATLAB environment. The predicted values are found to be in excellent agreement with the experimental data with average error value of 8%. In addition, we compared the proposed ANN model to another regression-based approach. Results show that the proposed model has high accuracy in comparison to statistical approach. Therefore, we can use ANN model to predict the part surface roughness for 3D printing technology.**

Index Terms: **3D printing ,Surface roughness ,Artificial neural network , The Back propagation network , the Multi-regression model.**

I. INTRODUCTION

From the last decade, additive manufacturing (AM) has been evolving rapidly and has displayed a great potential for energy-saving and cleaner environmental production due to a reduction in material and resource consumption and other tooling requirements [1]. In this modern era, with the advancements in manufacturing technologies, academia and industry have been given more attention to smart manufacturing for taking benefits for making their production more sustainable and effective [1].

Among various manufacturing technologies, 3D printing technologies, or its other synonyms such as additive manufacturing (AM), solid free form (SFF) or Rapid Prototyping (RP), is a process of joining the material technique used to create an object/part from three-dimensional (3D) digital model data, usually layer-by-layer (layer manufacturing), without tools, die casting, fixtures or even human intervention [2], which was first described in 1986 by Charles Hull, and then commercialized in 1990 as RP technology [3].

This technology creates parts by adding engineering materials rather than removing materials in order to reduce wastage while reaching a good surface finish quality of an item, with a reduction in the cost of production due to a lack of manufacturing tools, and has grown substantially in both volume and scope [4]. As mentioned above, there are a number of additive manufacturing (3D printing) techniques. The most frequent used is the FDM, in which the 3D printer machine heats the solid plastic filament, melts, and extrudes, it builds layer-by-layer to form the final product. The thickness of layers can vary between 0.1 to 0.5 mm, depending on the 3D printer setting. The most common 3D printer materials used in the FDM are Polylactic Acid (PLA) and Acrylonitrile-Butadiene-Styrene (ABS). Although both materials are used for FDM, they have key differences that make each more optimal for different applications [5].

Surface finish quality is crucial not only for improved functionality and appearance but also for cost-effectiveness and overall prototyping time reduction. As the AM process is performed using a layered manufacturing technique, one of the most important disadvantages of this process that the surface roughness of the printed part is excessively rough, especially when compared to other processes. The poor surface finish qualities observed in end products of the AM process has mainly been due to the layer upon layer deposition of the building process and is also influenced by tessellation of the original CAD model. A precise characterization of surface roughness is of prime importance in many engineering industries [4].

For this reason, the surface roughness (Ra), is a key issue in AM. To ensure better surface integrity, attention must be given to the selection of the manufacturing process parameters and measuring direction. Moreover, warping is one of the most common problems in AM due to material shrinkage which causes the corners of an object to lift and eventually detach from the build plate [6,7]. In the age of global competitiveness, it is very important to optimize the machining parameters that can reduce machining cost and time and increase productivity to obtain desired product quality. Effective machining parameter's optimization demands appropriate models for prediction of surface roughness in machining [8].

A number of previous works have focused on the use of classification techniques in additive manufacturing processes. Wu et al. [9] applied random forest, k-nearest neighbor, and anomaly detection techniques to detect defects caused by a cyber-attack on a Fused Deposition Modeling (FDM), 3D Printing printer during part fabrication.

Galantucci et al. [10] studied the effects of various machining parameters on the surface roughness of 3D roughness of parts built by Fused Filament Fabrication (FFF). The predictive modeling approach was demonstrated on a set of experiments. Boschetto and Bottini [12] developed a model that can estimate the surface roughness of the parts built by FFF and barrel finishing operations. The analytical model was validated using a set of experimental datasets. Reeves and Cobb [13] developed an analytical model of the surface roughness of the parts built by the stereo lithography process. The effects of layer thickness, surface angle, layer profile angle, up-facing layer composition, and down facing layer composition on surface roughness was studied.

Galantucci et al. [14] investigated the influence of various FDM machining parameters on acrylonitrile butadiene styrene (ABS) prototypes surface finish. A number of experimental works was conducted to study the influence of layer thickness and raster width on surface roughness.

Lyu et al. [15] tried to develop predictive models for surface roughness in the fused deposition modeling process taking into consideration layer thickness, temperature of extruder, and infill density. A regression-based, ANN, and Support Vector Machine - Regression (SVR) models were used to achieve their results. Their proposed models were used to characterize the relationship between the input variables and the surface roughness of fabricated parts. The results show that their approach using ANN model performed better than the multivariate linear regression and SVR models.

As stated in the literature, it is very important to predict and control the surface roughness of additively manufactured parts [6]. Many factors such as layer thickness, print orientation and print speed affect surface roughness. In this context, in order to improve the surface integrity of additively manufactured parts, a data-driven predictive modeling approach to predicting surface roughness in AM could be implemented.

The goal of this paper is to make the artificial neural network readily applicable to predict and control FDM parts surface roughness with minimal effort. Data needed for development of the models are obtained from the literature. In this work, the dataset from [19] will be used for building two surface roughness prediction models: a regression-based model and ANN model. Comparisons of the predicted surface roughness with that using AI techniques have been made in this paper. This paper is organized as follows: in the next section, i.e. Section 2, the theoretical background of ANN is described Section 3 shows the data we use for our investigations. In Section 3.2, we test and validate the proposed models in Section 3.1. Finally, conclusions and further research aspects are discussed in Section 4.

printed parts. A set of experiments was conducted to study the effects of layer thickness and raster width on surface roughness. Boschetto et al. [11] developed a predictive modeling approach to estimating the surface

II. ARTIFICIAL NEURAL NETWORK

Neural networks generally consist of neural units linked together by connections (as shown in Figure 1). These connections have an adjustable weight as a result of the training process, and each module is integrated into the model independently due to the information provided by the connection points. Linear or non-linear functions are used where the concepts of linear algebra are used to activate them. A great similarity can be observed between neural models and the general linear model developed by statisticians. For nonlinear neural networks, their behavior is determined by optimization and approximation techniques, including: hopfield network, boltzmann machine, backpropagation network, and radial basis function network [16].

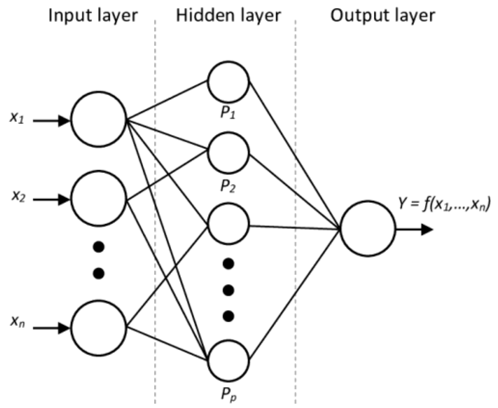

Figure 1. A Neural network.

A. *The Backpropagation network (BP)*

The back-propagation method of Rumelhart, hinton, and Williams (1986a) is a method of training multi-layer neural networks where the network can learn to assign a set of inputs to a set of outputs, so that the learning is done by recursively adjusting the weights of the neural points in the network.

In the beginning, small random weights are given to give results that are compared with the target, and when there is an error, it is backwards through the network to adjust the new weight, and the process is repeated in the same way until we reach the required accuracy in the results [17]. Figure 2 shows the structure of this model.

This method is one of the most popular neural network algorithms. Rojas [2005] claimed that this algorithm can be divided into four main steps after choosing the initial weights randomly so that the algorithm corrects these weights until it reaches the desired goal. These steps are as follows:

i) Feed-forward computation
ii) Back propagation to the output layer
iii) Back propagation to the hidden layer

iv) Weight updates

The algorithm stops when the error function value becomes small enough [18].

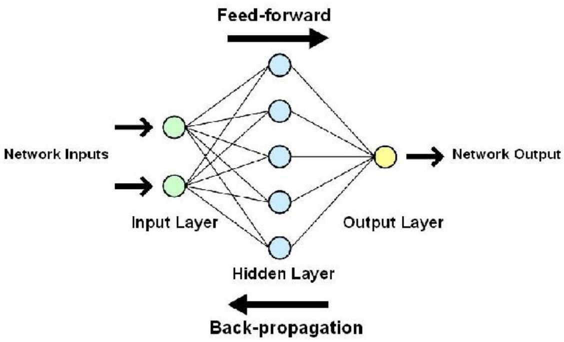

Figure 2. The Back propagation network (BP)

III. RESULTS AND DISCUSSION

In this paper, two methods were used to predict the surface roughness, the first method was the regression-based analysis method, and the second method was the Artificial Neural network (ANN) method. The simulation experiments were conducted using Matlab environment. For fair comparison, the same dataset was used in comparison. In order to optimize the proposed models; Nozzle temperature (C□), layer height (µm), printing speed (mm/s), Nozzle diameter (mm), and Infill density (%) are considered as input variables, and the surface roughness (µm) is considered as the output (see Table 1).

The available data set in Table 2 is divided into two parts; 70% of the data was used as a training dataset, and 30% was used to verify the validity of the models.

Table 1. The symbols used in the tables

Parameter	Definition	Unit
NT	Nozzle temperature	C□
LH	layer height	µm
PS	Printing speed	mm/s
ND	Nozzle diameter	mm
ID	Infill density	%
RA	Roughness	µm

Table 2. Experimental results [19].

No	NT	LH	PS	ND	ID	RA
1	210	200	30	0,3	30	42,7
2	190	150	75	0,4	20	26,2
3	190	200	30	0,5	10	54
4	200	200	75	0,4	20	30,5
5	190	100	120	0,5	10	25
6	190	100	120	0,3	10	18,3
7	190	100	30	0,3	10	26,3
8	210	100	30	0,3	30	24,8
9	190	100	120	0,3	30	16
10	190	100	30	0,5	10	34,1
11	190	200	120	0,3	30	29,6
12	200	150	120	0,4	20	27,8
13	210	150	75	0,4	20	30,6
14	210	100	120	0,5	10	29,3
15	210	100	30	0,3	10	51,8
16	210	200	120	0,3	30	34
17	210	100	120	0,5	30	23,7
18	210	200	30	0,5	10	58
19	200	150	75	0,4	10	33,3
20	210	100	30	0,5	10	38
21	190	100	30	0,3	30	21
22	210	200	120	0,5	30	43,6
23	210	200	120	0,3	10	39,6
24	210	200	120	0,5	10	49,1
25	210	200	30	0,3	10	48,9
26	200	150	75	0,5	20	33,1
27	210	200	30	0,5	30	52,3
28	210	100	30	0,5	30	32,4
29	190	200	30	0,5	30	48,6
30	210	100	120	0,3	30	17,6

A. *Development of the Multi-regression model*

Linear regression is the simplest technique to correlate inputs with resulting surface roughness. A Least Squares (LS) approach can be used to obtain the coefficients that determine the relationship between inputs and output without using any physical equation. Although this method can provide reasonable results for some scenarios, the surface roughness usually changes with variation in the printing process, which introduces an error into the model. For establishing the prediction model, a software package EXCEL 2016 was used to perform the model with the obtained results. The coefficients of the equation required for the prediction model were illustrated in Table 3

Table 3. The coefficients of the equation

Parameter	Coefficients
Intercept	-49,5846
Nozzle temperature	0,32286
layer height	0,15585
Printing Speed	-0,11815
Nozzle Diameter	28,12675
infill density	-0,342623

Regression equation is as follow:

$$R = 0{,}32286NT + 0{,}15585LH - 0{,}11815PS + 28{,}1268ND - 0{,}34262ID - 49{,}5846 \quad (1)$$

After the model was built, it will be validated against experimental results in the next section. However, the same data are used to transform the outputs into the ANN model to search whether or not any improvement can be achieved with this new approach.

B. Development of the ANN model

In order to assess the ability of the regression-based model relative to that of a neural network model, an ANN model was constructed using the same input variables to the regression-based with 6 inputs. For the proposed neural network modeling approach, the datasets were also divided into the similar two groups of sets for training, and testing. It is worth noting that the range of the training data must be representative of the entire operating conditions of the 3D printer in order to overcome the problem of extrapolation error.

Selection of the number of neurons in the hidden layer is important for finding a suitable ANN model structure. Although increasing the neuron numbers in the hidden layer, may help to improve the neural network performance , however, the possibility of over-fitting may increase. Furthermore, a large number of hidden neurons can increase model training time. In this work, the minimum MSE (see Figure 3) is determined by changing the number of hidden neurons. Therefore, after a series of experiments to find the best architecture, an ANN model with 3 neurons in the hidden layer and after 300 iterations was constructed to predict the surface roughness. Figure 4 shows the structure of associated network model.

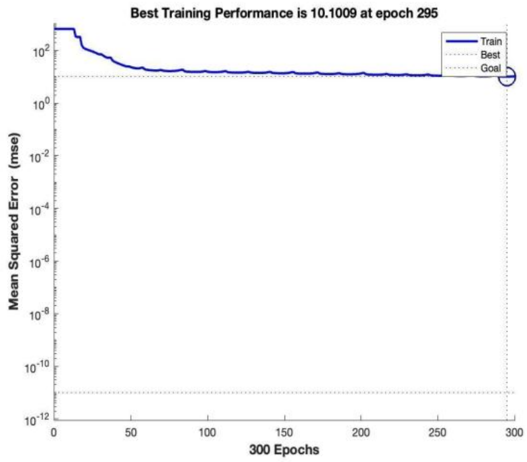

Figure 3. The training performance

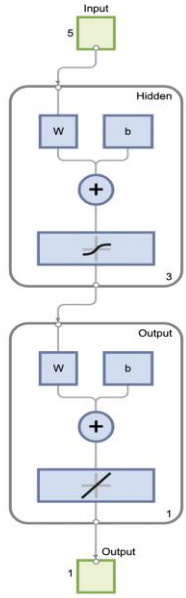

Figure 4. The structure of the associated network model.

C. Validation of the proposed models

In this section, the aim is to use the structure of the two models described in the previous sections to predict the surface roughness. With the purpose of evaluating the prediction performance of the models, the remaining data set (testing data set) was used to run the proposed models. The performance of the models used in this study was computed using percentage error E_i and average percentage error E_{av} defined in equations (2) and (3), respectively, as follows:

$$E_i\% = \frac{|Ra_{Exp} - Ra_{Pre}|}{Ra_{Exp}} \times 100 \qquad (2)$$

$$E_{av}\% = \frac{1}{m}\sum_{i=1}^{m} E_i \qquad (3)$$

Where Ra_{exp} and Ra_{pre} stands for experimental values and predicted values, respectively; m is the sample number to be predicted.

Also, the correlation coefficient R was used to evaluate the performance of these models, as it gives basic information about the relationship between the variables. Here, the correlation coefficient between each of the measured value and the predicted value of the surface roughness was calculated to determine the extent of convergence of the results, and to calculate R the following equation (4) is used:

$$R = \frac{m(\sum Ra_{Pre} Ra_{Exp}) - (\sum Ra_{Pre})(\sum Ra_{Exp})}{\sqrt{[m\sum {Ra^2}_{Exp} - (\sum Ra_{Exp})^2][m\sum {Ra^2}_{Pre} - (\sum Ra_{Pre})^2]}} \qquad (4)$$

Where Ra_{exp} and Ra_{pre} stands for experimental values and predicted values, respectively; m is the sample number to be predicted. Predictive results using regression-based, and ANN models are shown in Table 4. The performance of each of the two surface roughness models is presented and compared, where the two models are trained using the same training dataset and validated by the same testing dataset.

According to the predictive results and evaluation criteria values in Table IV, it is very clear that the ANN model has a smaller average error (8%), and higher correlation coefficient (R=96%) contrasting with the regression-based model. It can be also observed from Table IV that the model developed using the artificial intelligence techniques outperformed the statistical model (regression-based model). Therefore, the ANN model is a good modeling choice for predicting the surface roughness of the 3D printer with the benefit of fewer parameters.

Table 4. Comparison of predictive results

Test No.	Ra	Results of the proposed models			
		Regression-based		ANN	
	Measured	Predicted	Error(%)	Predicted	Error(%)
1	20,5	24,63484	20.17	21,9029	6.84
2	19	26,10947	37.42	21,0651	10.87
3	35,3	33,76264	4.36	35,295	0.01
4	23,9	31,08929	30.08	23,2365	2.78
5	27,7	30,47577	10.02	21,9471	20.77
6	28	33,90197	21.08	26,283	6.13
7	36,9	39,21872	6.28	41,5968	12.73
8	45	39,388	12.47	45,1598	00.36
9	38,8	37,54374	3.24	35,8606	7.58
10	44,3	44,39614	0.22	39,2559	11.39
11	20,2	16,9506	16.09	21,1164	4.54
12	28,7	27,5841	3.89	23,4941	18.14
13	43,1	32,5356	24.51	42,2378	2.00
Average percentage error E_{av}			14.6%		8%
The correlation coefficient R			0.84		0.96

IV. CONCLUSIONS

In this work, an artificial neural network system for the modelling and prediction of the part surface roughness for 3D printing technology is presented. The comparison between experimental and predicted values of the proposed ANN model shows that there is an excellent agreement between the predicted surface roughness and the experimental results with average error values of 8% and correlation coefficient of 96%. This means that the proposed model can simulate the part surface roughness for 3D printing process with excellent level of accuracy and lower neurons. The results obtained with the proposed ANN model is also superior to regression-based model.

REFERENCES

[1] A Majeed, Y Zhang, S Ren, J Lv, T Peng ,A big data-driven framework for sustainable and smart additive manufacturing, Robotics and Computer Integrated Manufacturing, February 2021, 102026

[2] Wang, X., et al., 3D printing of polymer matrix composites: A review and prospective. Composites Part B: Engineering, 2017. 110: p. 442-458.

[3] Hull, C. W., Apparatus for production of three-dimensional objects by stereolithography. 1986, Google Patents.

[4] Mohammad S. Alsoufi*, Abdulrhman E. Elsayed, How Surface Roughness Performance of Printed Parts Manufactured by Desktop FDM 3D Printer with PLA+ is Influenced by Measuring Direction. Department of Mechanical Engineering, College of Engineering and Islamic Architecture, Umm Al-Qura University, Makkah, KSA *Corresponding author: mssoufi@uqu.edu.sa

[5] Satish Chinchanikar a, Sourabh Shindeb, Vaibahv Gaikwadc, Avez Shaikha, Mayur Rondhed and Mohit Naike.ANN modelling of surface roughness of FDM parts considering the effect of hidden layers, neurons, and process parameters.aDepartment of Mechanical Engineering, Vishwakarma Institute of Information Technology, India; bDepartment of Mechanical Engineering, College of Engineering Pune, India; cEngineering Education and Research, K.K. Wagh Institute, Nashik, India; dDepartment of Mechanical Engineering, Pimpri Chinchwad College of Engineering, Pune India; eDepartment of Computer Science, Vishwakarma Institute of Technology Pune, India,2022.

[6] Farzaneh Kaji*, Ahmad Barari**, Evaluation of the Surface Roughness of Additive Manufacturing Parts Based on the Modelling of Evaluation of the Surface Roughness of Additive Manufacturing Parts Based on the Modelling of Cusp, University of Ontario Institute of Technology, L1H 7K4, Oshawa, Ontario ** Canada (e-mail: farzaneh.kaji@ uoit.ca)

[7] Donghwan Song, Adrian Matias Chung Baek, Jageon Koo, Moise Busogi 3 and Namhun Kim, Forecasting Warping Deformation Using Multivariate Thermal Time Series and K-Nearest Neighbors in Fused Deposition Modeling, Received: 24 November 2020; Accepted: 14 December 2020; Published: 15 December 2020

[8] P.G. Benardos, and G.-C. Vosniakos, "Predicting surface roughness in machining: a review." International Journal of Machine Tools and Manufacture, 43, 833–844 (2003).

[9] Juan M. Barrios and Pablo E. Romero, Decision Tree Methods for Predicting Surface Roughness in Fused Deposition Modeling Parts, Materials (Basel). 2019 Aug; 12(16): 2574. Published online 2019 Aug 12. doi: 10.3390/ma12162574

[10] Zhixiong Lia Ziyang Zhang aJunchuan Shia Dazhong Wub, Prediction of surface roughness in extrusion-based additive manufacturing with machine learning, Robotics and Computer-Integrated Manufacturing ,Volume 57, June 2019, Pages 488-495

[11] A. Boschetto, V. Giordano, F. Veniali, 3D roughness profile model in fused deposition modelling, Rapid Prototyping J. 19 (4) (2013) 240–252.

[12] Alberto Boschetto,Luana Bottini.Roughness prediction in coupled operations of fused deposition modeling and barrel finishing.Sapienza University of Rome,Journal of Materials Processing Technology 219 DOI:10.1016/j.jmatprotec.2014.12.021

[13] P.E. Reeves, R.C. Cobb, Reducing the surface deviation of stereolithography using in-process techniques, Rapid Prototyping J. 3 (1) (1997) 20–31.

[14] Lyu J, Manoochehri S. Dimensional prediction for FDM machines using artificial neural network and support vector regression. InInternational Design Engineering Technical Conferences and Computers and Information in Engineering Conference 2019. (Vol. 59179, p. V001T02A033). American Society of Mechanical Engineers. America

[15] Galantucci, Luigi Maria, Fulvio Lavecchia, and Gianluca Percoco. "Experimental study aiming to enhance the surface finish of fused deposition modeled parts." CIRP annals 58.1 (2009): 189-192.

[16] HERVE ABDI. A Neural network primer. School of Human Development: The University of Texas at Dallas.Ms: GR.4.1.Richardson,TX75083-0688, USA. université de bourgogne à dijon,2100,dijon,france.1994.

[17] 1 A VAN OoYEN,2 B.NiENHUIS .Improving the Convergence of the Back-propagation Algorithm.1 Netherlands Institute for Brain Research,2 University of Amsterdam.1991.

[18] Mirza Cilimkovic,Neural Networks and Back Propagation Algorithm .Institute of Technology Blanchardstown ,Blanchardstown Road North Dublin 15, Ireland, mirzac@gmail.com

[19] Mohammad Shirmohammadi1 · Saeid Jafarzadeh Goushchi1 · Peyman Mashhadi Keshtiban2.Optimization of 3D printing process parameters to minimize surface roughness with hybrid artificial neural network model and particle swarm algorithm.Urmia University of Technology.Received: 12 July 2020 / Accepted: 19 January 2021 © The Author(s), under exclusive licence to Springer Nature Switzerland AG part of Springer Nature 2021 .